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Dynamic Error-Correlation Adaptive Weighting for Hybrid Energy Consumption Forecasts

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Abstract. Accurate energy consumption forecasting is essential for grid stability, operational planning, and resource optimization. This study investigates the effectiveness of hybrid forecasting strategies by combining four widely used time series models ARIMA, ETS, THETAM, and NNETAR and proposes a Dynamic Error-Correlation Adaptive Weighting (DECAW) mechanism for ensemble construction. The proposed framework integrates recency-weighted validation errors and explicit penalization of forecast error correlation to enhance diversification and robustness. Using a dataset of electricity consumption collected from a medium-sized Romanian city, the performance of individual models and hybrid approaches was assessed and compared. Results reflect the dominance of linear seasonal dynamics in the dataset. Hybrid models produced competitive results, with DECAW yielding the lowest hybrid MAPE and MAE and marginally improving upon conventional cross-validated weighting. DECAW consistently redistributed weights toward structurally complementary components and reduced the influence of correlated or unstable predictors. The findings demonstrate that correlation-aware adaptive weighting enhances ensemble stability and robustness, particularly in moderately complex seasonal systems.

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Key words and phrases. energy consumption forecasting, hybrid forecasting models, time series analysis, adaptive weighting, forecast error correlation.

1. Introduction

Energy consumption forecasting represents a key element for efficient energy management considering a world wide continuous increasing energy demand. Taking into account both long-term predictions used for infrastructure planning or daily necessity estimates that help support electrical grid stability, accurate forecasting ensures the cost optimization, the stability between supply and demand, and a minimal repercussion over the environment. Energy systems are frequently influenced by circumstances like the increase in renewable energy options, economic activity, weather conditions or consumer behavior, leading to an increased complexity of these systems which, in turn, creates various challenges in the process of forecasting.

Conventional forecasting techniques, such as linear regression [1] and autoregressive integrated moving average [2], have been extensively applied in the energy consumption field, obtaining good results in identifying trends and seasonality [3]. However, they usually fail to capture non-linear features considering the high volatility observed in modern energy data. These features can be successfully addressed by machine learning models [4] such as artificial neural networks [5] or support vector machines [6].

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Although these traditional methods are perfect for non-linear aspects, they may miss the precision and clarity that are essential in the process of time-series forecasting. For example, regular patterns in energy consumption may be altered during holidays or weekends and this trend may not be accurately predicted by linear models. Traditional models don't have enough flexibility in adapting to unforeseen modifications in datasets and may underperform in cases such as unexpected energy supply disruptions or unseasonal weather conditions.

A promising solution is to develop hybrid models [7] that combine both the statistical and machine learning approaches using their best features to acquire the forecasting accuracy. The challenges of the seasonal, high-dimensional and non-linear nature of data are effectively addressed by the hybrid models especially for energy consumption forecasting. Hybrid approaches deliver strong and reliable predictions, even in complex scenarios, by combining the trend-handling capabilities of statistical models with the flexibility of machine learning techniques.

Fluctuations in weather conditions lead to irregular seasonal variations in energy demands [8], while industrial production and developing consumer behavior create the complexity of the energetic system. Renewable energy sources [9] depending on factors like wind speed or solar irradiance offer variability in energy consumption datasets such as non-linear trends or sharp peaks. Thus, each of these factors uniquely contribute to unpredictable fluctuations in energy consumption patterns.

Statistical models that analyze and predict energy consumption patterns also include supplementary forecasting factors such as humidity, temperature, period of day, sunlight duration or economic aspects [10]. Taking all these factors into account, the datasets used in predictive models are multidimensional, making it difficult for traditional models to comprehend all of the meaningful and complex features of such input data [11]. The gaps in traditional methods are resolved by hybrid models which unify several complementary forecasting approaches, providing more accurate predictions for energy consumption [12].

Hybrid models usually incorporate a dual-layer approach in order to exploit all aspects of the datasets, for example, ARIMA model could be used for analyzing the linear and seasonal trends, on one side, while machine learning models (ANN or SVR) could be used for handling the nonlinear patterns. The machine learning part of the hybrid model can easily adapt to real-world data, dynamically adjusting to nonlinear relationships. Reduction of forecasting errors is handled by the machine learning component of the hybrid model. For example, the ARIMA-LSTM hybrid model [13] provides lower residual errors than each of the models applied separately. Hybrid models manage to adapt to data seasonality from the energy consumption datasets including specific forecast factors and variations. For instance, wavelet analysis could be used for energy consumption time series decomposition into seasonal and nonlinear components and then, together with the LSTM model, obtaining a better nuanced forecast [14].

Noisy or incomplete data is better handled by hybrid techniques that integrate multiple methods reducing the possibility of underperforming or overfitting, creating a shield against variability [15]. Using multiple methods in hybrid models is also facilitated by automation, advanced computational power, machine learning frameworks and artificial intelligence techniques.

Hybrid models, with both statistical and machine learning components, address energy consumption forecasting challenges in complex and dynamic systems. Besides improving forecast accuracy, these models facilitate better planning and decision-making for grid operators, policymakers, and energy companies, thus better handling the rapidly evolving energy domain [16].

The growing demand for advanced forecasting techniques is generated by the constant evolution of energy systems that integrate smart technologies and energy from undepletable sources. This need is fulfilled by hybrid prediction models that are able to deal with dynamic patterns and complex datasets, having also the ability to evolve and adjust in time. The precision and adaptability of these models are guided by advancements in computational power and artificial intelligence. The complex datasets used in predictive models consist of real time data collected from various IoT devices and sensors. Nowadays technologies allow hybrid models to analyze information in real time for an instant updated and accurate forecast, such as the prediction of smart grids hourly energy demand based on historical data and sensor inputs [17].

The artificial intelligence techniques [18] associated with hybrid models consist of reinforcement learning (forecasting optimization by learning from real time feedback), adaptable architectures (the ability to model stable dependencies in multidimensional data) and explainable AI (tools for improvement of transparency and trust).

Addressing challenges such as grid balancing, microgrid optimization and renewable energy forecasting, grant hybrid models an important role in the integration of renewable energy. Hybrid models that forecast both energy demand and renewable supply can be used for dynamic grid balancing, ensuring a stable and reliable power supply both globally and at the community level.

Modern forecasting implies handling large datasets via cloud services and big data technologies [19] and is accomplished using hybrid models trained on sensitive customer information without compromising data privacy that is a crucial aspect of energy systems [20]. These tasks are achieved with the help of high-performance computing that allow faster algorithms and datasets processing in order to reduce forecasting computation time.

Efficiently managing the energy supply and demand is achieved by hybrid models that aggregate regression and neural networks applied in distributed energy systems [21]. In such decentralized grids the main focus falls on local forecasting, household energy demand and solar panel supply establishing a residential microgrid. For example, in order to reduce peak loads, predictions of consumption patterns should improve the system demand requirements as well as energy storage optimization (batteries energy load and release) ([22], [23]).

Designing a hybrid model demands significant expertise and is a complex process taking into account their close integration with real time energy management systems [24]. These models are created in such a way that they can satisfy multiple objectives simultaneously [25] such as improved accuracy, computational efficiency, and minimized forecasting errors.

Hybrid models for forecasting energy are designed towards increasing adaptability and integration. The growing complexities of modern energy systems are addressed by advancements in real-time data processing, artificial intelligence techniques, and computational power. As these technologies continue to evolve, hybrid models will play an essential role in implementing smarter, more efficient, and sustainable energy management strategies.

In this paper we examine the concept of hybrid models and their application in the energy consumption forecasting domain. We combine four forecasting models (ARIMA [26], ETS [27], THETAM [28], and NNETAR [29]) to obtain a hybrid model, **Dynamic Error-Correlation Adaptive Weighting (DECAW)**, leveraging the strengths of each component and we discuss its advantages compared to traditional techniques. The proposed DECAW mechanism is compared to conventional cross-validated error weighting approach [30]. We present a practical example of the hybrid model's implementation using a dataset representing energy consumption in a Romanian medium-sized city. DECAW is a correlation-aware hybrid weighting framework that extends traditional inverse-error approaches by explicitly incorporating error covariance and recency sensitivity. The obtained results can be further used by energy providers and policymakers to develop a smart energy management system.

2. Methodology

Hybrid frameworks can readjust to dynamically changing data, scale the datasets and provide immediate predictions by integrating real-time neural networks and reinforcement learning. A particular value of these models is their dual-layer interpretability given by their two components: the statistical factor dealing with traditional and seasonal data and the machine learning element relative to anomalies and arising patterns. Efficient energy forecasting is especially important for resource optimization, cost minimization, and effective grid management by decreasing the redundant energy production or storage.

Hybrid models are built in various ways and through different techniques, depending on individual methods combination, thus obtaining sequential, parallel, decomposition based or optimisation enhanced hybrid models. In this research we focused mainly on the parallel hybrid models by combining the outputs of multiple models applied individually on the collected dataset, a task that is achieved using weighted average of the results.

This study proposes a hybrid forecasting framework that integrates linear stochastic modeling, exponential smoothing, curvature-adjusted trend decomposition, and nonlinear neural modeling for energy consumption prediction.

The dataset used in this study comprises 18 years of energy consumption monthly values, measured in gigawatt-hours (GWh), collected from a medium-sized Romanian city, covering the period from 2008 to 2025. The dataset, having strong autocorrelation and nonlinear demand-response effects, was obtained from the local electricity distribution operator of the municipality and comprises energy consumption from residential, public services and industrial sectors. In Figure 1 we can easily observe the multiple seasonality and the deterministic and stochastic trend of the dataset.

Let $y_{t}{}_{t=1}^{T}$ denote the univariate energy consumption time series observed at equally spaced intervals, $\hat{y}_{t+h|t}$ = forecast at horizon (h), $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$ white noise.

Our proposed hybrid forecasting framework integrates four complementary models, each one capturing distinct structural properties of the time series:

$$\mathcal{M} = \{\mathrm{ARIMA}, \mathrm{ETS}, \mathrm{THETA}, \mathrm{NNETAR}\}$$

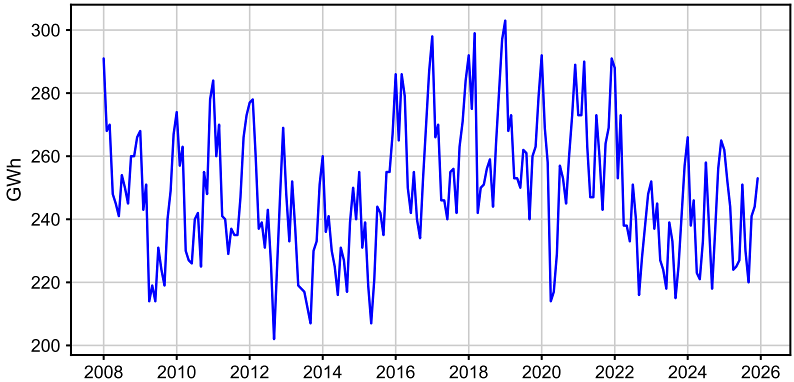

FIGURE 1. Energy consumption trend.

- the linear stochastic component
  The AutoRegressive Integrated Moving Average model $ARIMA(p, d, q)$, captureing short-term linear dependence and shock propagation in demand dynamics, is defined as:
$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$$
  where: B is the backshift operator $By_t = y_{t-1}$, $(1-B)^d$ is the differencing operator $\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$, $\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$.
- the state-space exponential smoothing
  The ETS model (Error Trend Seasonality) provides adaptive smoothing and dynamic updating of structural components. The observation equation is:
$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$
  and the state update equations are:
$$\begin{aligned} \ell_t &= \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t \\ b_t &= b_{t-1} + \beta\varepsilon_t \\ s_t &= s_{t-m} + \gamma\varepsilon_t \end{aligned}$$
  where: $\ell_t = level$, $b_t = trend$, $s_t =$ seasonal component, $\alpha, \beta, \gamma \in (0, 1)$.
- trend-curvature decomposition
  The Theta method, particularly effective for long-horizon energy demand projections, modifies local curvature through a parameter θ:
$$y_t^{(\theta)} = \theta y_t + (1-\theta)\hat{y}_t^{(LR)}$$
  where $\hat{y}_t^{(LR)}$ is the linear regression trend estimate.
- nonlinear autoregressive component
  To capture nonlinear dynamics, we used NNETAR to approximate nonlinear load patterns and complex consumption elasticity:
$$y_t = f(y_{t-1}, \ldots, y_{t-p}, y_{t-s}, \ldots) + \varepsilon_t$$

with neural network approximation:

$$\hat{y}_t = \beta_0 + \sum_{k=1}^{K} \beta_k \sigma \left(w_{k0} + \sum_{i=1}^{p} w_{ki} y_{t-i} \right)$$

where: K = number of hidden neurons, $\sigma(\cdot)$ = activation function, w_{ki}, β_k = weights.

The proposed hybrid forecast formulation provides a unified, statistically grounded, and computationally implementable framework for accurate energy consumption forecasting and is defined as a convex combination:

$$\hat{y}_{t+h} = w_1 \hat{y}_{t+h}^{ARIMA} + w_2 \hat{y}_{t+h}^{ETS} + w_3 \hat{y}_{t+h}^{THETA} + w_4 \hat{y}_{t+h}^{NNETAR}$$

with: $\sum_{i=1}^{4} w_i = 1$.

Traditionally, forecasting hybrid models use equal weights, or compute weights based on inverse RMSE or constrained least squares. These methods have limitations in time-varying model performance and don't take into account error correlation between models.

We propose a Dynamic Error-Correlation Adaptive Weighting (DECAW) method, described in Algorithm 1. In this method, the weights are computed from the raw weights normalization. For each validation window we compute the rolling validation errors, the exponentially weighted errors and the pairwise correlation that allows us to estimate the raw weight score. This approach rewards low recent error, encourages diversity while sanctioning correlated forecasts.

3. Results and Discussion

The experimental protocol was designed to quantify the accuracy gains of the proposed DECAW hybrid framework over strong individual baselines, evaluate robustness across horizons and seasonal regimes, and validate its weighting contribution relative to standard ensembling.

We intended to test if the hybrid forecast $\hat{y}^{HYB}$ yields lower error than each individual model $\hat{y}^{(i)}$ in terms of computed accuracies across horizons (h), if DECAW achieves lower error than the cross-validation error hybrid approach as well as if it has the capacity to maintain performance under regime shifts (trend changes), outliers, and increased error correlation among components.

The dataset we used consists of 216 monthly observations and a holdout of 24 months was applied for out-of-sample evaluation, while the remaining observations were used for model training. Four individual models (ARIMA, ETS, THETAM, NNETAR) and two hybrid approaches (cv.errors weighting and the proposed DECAW weighting) were compared. After training and testing the models we computed the accuracy metrics in order to make the evaluation and comparison.

Table 1 summarizes the test-set performance of the four individual models and the two hybrid approaches. We observe that DECAW hybrid method obtained slightly improved performance compared to the other hybrid model and visibly outperforms the individual models.

Algorithm 1 DECAW Hybrid Energy Forecasting

Input Time series $\{y_t\}_{t=1}^T$,
forecast horizon H, validation window V, decay factor λ
Output Hybrid forecast $\{\hat{y}_{T+h}\}_{h=1}^H$
Define rolling validation window over last V observations
for each model $i \in \{\text{ARIMA}, \text{ETS}, \text{THETA}, \text{NNETAR}\}$ **do**
Fit model i using training subset
Generate validation forecasts
Compute validation errors $e_{i,t} = y_t - \hat{y}_{i,t}$
end for
for each model i **do**
Compute exponentially weighted error

$$E_i = \sum_{k=1}^{V} \lambda^{k-1} e^2_{i,T-k+1}$$

Compute correlation penalty

$$D_i = \sum_{j \neq i} |\text{Corr}(e_i, e_j)|$$

Compute raw score

$$u_i = \frac{1}{E_i} \cdot \frac{1}{1 + D_i}$$

end for
Normalize weights

$$w_i = \frac{u_i}{\sum_j u_j}$$

Refit all models on full dataset $\{y_t\}_{t=1}^T$
Generate H-step forecasts $\hat{y}_{T+h}^{(i)}$ for each model i
Combine forecasts:

$$\hat{y}_{T+h}^{HYB} = \sum_i w_i \hat{y}_{T+h}^{(i)}, \quad h = 1, \ldots, H$$

return $\{\hat{y}_{T+h}^{HYB}\}_{h=1}^H$

Table 1. Test set accuracy (24-months holdout).

Model	**RMSE**	**MAE**	**MAPE (%)**
ARIMA	8.742	6.383	2.622
ETS	10.014	7.571	3.111
THETAM	9.328	6.765	2.756
NNETAR	14.382	11.085	4.711
Hybrid cv.errors	8.295	6.300	2.574
Hybrid DECAW	**8.288**	**6.250**	**2.550**

The empirical results indicate that the ARIMA model achieved the lowest out-of-sample RMSE (8.742) among all individual models. This finding suggests that the

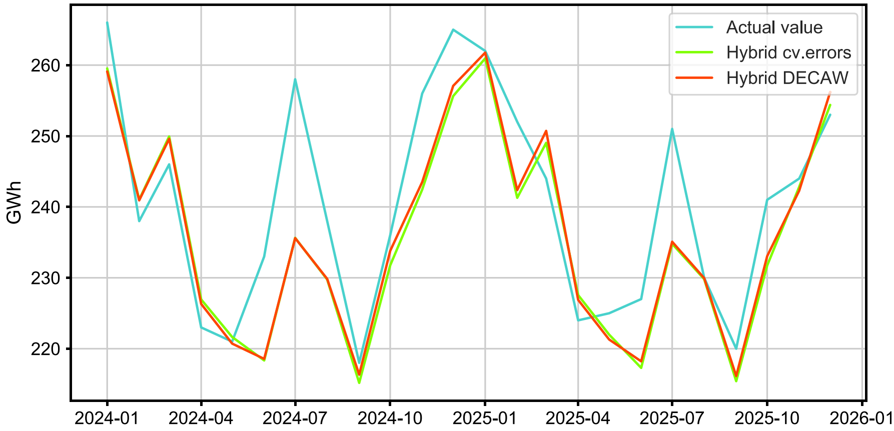

FIGURE 2. Forecast vs Actual (test period).

underlying energy consumption process is predominantly governed by linear autoregressive and seasonal dynamics. The relatively low MAPE (2.62%) confirms strong periodic regularity and stable stochastic dependence.

ETS underperformed relative to ARIMA, suggesting that while exponential smoothing captures trend and seasonality adaptively, it lacks the stochastic structure modeling provided by seasonal ARIMA components.

THETAM demonstrated intermediate performance, reflecting its strength in capturing trend curvature but weaker modeling of short-term dependencies.

NNETAR exhibited substantially higher RMSE, indicating overfitting or limited nonlinear signal in the data. This suggests that nonlinear components contribute marginally to predictive improvement in this particular dataset. In such contexts, nonlinear models do not necessarily provide additional predictive power. The inferior performance of NNETAR indicates that the nonlinear structure of the database is relatively weak.

Both hybrid approaches produced competitive performance, but the proposed DECAW method slightly improved upon the conventional cross-validated weighting approach, reducing MAPE from 2.574% to 2.550% and marginally lowering RMSE. Figure 2 represents a comparison between both hybrid forecasts, DECAW and cv.errors, versus the test period trend. Hybridization guarantees superior performance over the component models and its theoretical advantage lies in variance reduction and robustness enhancement.

Importantly, based on the weights presented in Table 2, DECAW reallocated weights by increasing the contribution of THETAM and decreasing that of NNETAR relative to the cv.errors model. This redistribution reflects the error-correlation penalization mechanism embedded in DECAW. By discouraging redundant contributions from correlated models and downweighting unstable predictors, DECAW promotes diversification within the ensemble. The contribution of DECAW is not primarily dramatic accuracy increase, but improved structural stability and principled weight adaptation.

Table 2. Computed weights generated by the hybrid models.

Model	cv.errors weights	DECAW weights
ARIMA	0.233	0.244
ETS	0.280	0.281
THETAM	0.275	0.315
NNETAR	0.211	0.159

A key methodological insight emerges from the weight comparison. The correlation-aware adjustment in DECAW shifted weight away from NNETAR toward THETAM, slightly increasing ARIMA contribution. This suggests that neural model forecast errors were either unstable or correlated with other models in a way that did not contribute additional information. This redistribution reflects the correlation penalty embedded in DECAW, which downweights models with redundant error structures.

Ensemble theory shows that the variance of a weighted forecast:

$$Var\left(\sum_i w_i e_i\right) \sum_i w_i^2 Var(e_i) + 2 \sum_{i<j} w_i w_j Cov(e_i, e_j)$$

is reduced when covariance terms are minimized. By explicitly penalizing correlated error streams, DECAW attempts to optimize this trade-off.

In strongly seasonal linear systems such as the present dataset, ARIMA and ETS likely share similar error structures. DECAW's correlation penalty reduces over-representation of structurally similar components, contributing to ensemble stability.

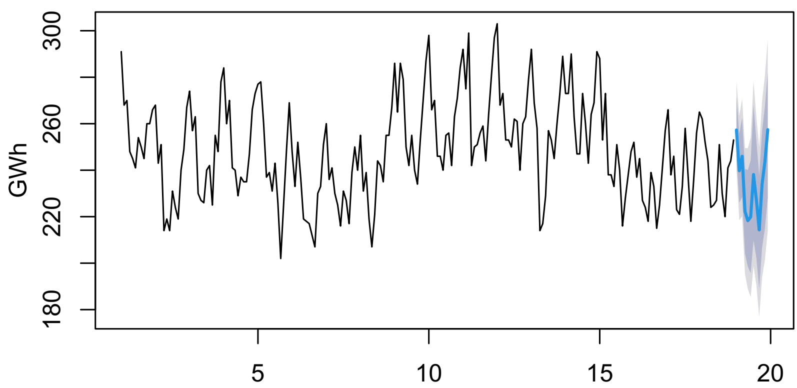

Figure 3. 12-months DECAW forecast.

The 12-months DECAW forecasts (Figure 3) display a clear and stable seasonal oscillation, with peak values observed during the winter months and lower levels in mid-year periods. The preservation of seasonal amplitude and phase alignment confirms that dominant seasonal dynamics remain the primary drivers of projected demand. As expected, prediction intervals widen gradually with the forecast horizon, reflecting increasing uncertainty over time.

Although the seasonal ARIMA model achieves strong standalone performance, the DECAW hybrid approach delivers consistently competitive results and improves upon conventional cross-validated weighting. By incorporating recency-weighted errors and penalizing correlated forecast structures, DECAW redistributes model weights toward structurally complementary components while limiting the influence of unstable predictors. This correlation-aware adaptation enhances ensemble stability and reduces redundancy among base learners.

While nonlinear contributions appear limited in this dataset, the DECAW framework demonstrates improved robustness and methodological rigor. The results suggest that adaptive, correlation-sensitive weighting becomes particularly valuable when model complementarity exists or when structural variability increases, positioning DECAW as a scalable and resilient solution for energy demand forecasting.

4. Conclusions

This study investigated the effectiveness of hybrid forecasting strategies for monthly energy consumption prediction using four widely adopted models, ETS, ARIMA, THETAM, and NNETAR, and introduced a novel Dynamic Error-Correlation Adaptive Weighting (DECAW) mechanism for ensemble construction. When energy demand exhibits stable seasonal dynamics, well-specified ARIMA models remain highly competitive. On the other hand hybrid models are particularly valuable when structural shifts occur, forecast horizon increases or nonlinear regime transitions appear. Adaptive weighting mechanisms such as DECAW enhance robustness under uncertainty, even when immediate accuracy gains are small.

In operational contexts (e.g., grid load planning), robustness and stability may be as important as marginal accuracy improvements. A slightly more stable forecast with lower sensitivity to model misspecification can reduce downstream risk.

The proposed DECAW hybrid model produced the lowest hybrid MAPE and MAE and slightly improved upon conventional cross-validated weighting. Although performance gains were modest, DECAW consistently reallocated weights toward structurally complementary components and penalized correlated forecast errors. This confirms the theoretical premise that ensemble improvement depends not merely on averaging accuracy but on controlling redundancy and error covariance.

From a methodological perspective, DECAW extends traditional inverse error weighting by integrating recency-sensitive validation and explicit correlation penalization. This dual mechanism enhances robustness and stabilizes ensemble behavior under structural uncertainty. The approach is computationally efficient, scalable, and adaptable to multi-horizon or multivariate forecasting contexts.

The primary contribution of this study does not lie solely in the marginal reduction of RMSE, but rather in the development of a structured and theoretically grounded weighting framework for hybrid forecasting. The proposed approach integrates three key mechanisms: recency-weighted validation errors to capture evolving performance, explicit penalization of forecast error correlation to mitigate redundancy, and dynamic weight adjustment to enhance adaptability across regimes.

This framework extends conventional inverse-error weighting by incorporating structural information about model interdependence and temporal stability. As such, it provides a more principled basis for ensemble construction. Moreover, the methodology is inherently flexible and can be readily extended to multi-horizon weighting schemes, probabilistic forecast combinations, and multivariate load forecasting environments.

Future research should evaluate DECAW on higher-frequency datasets, incorporate exogenous variables such as weather and price signals, and extend the framework to probabilistic forecasting and multivariate load modeling. Such developments will further enhance its applicability in modern smart grid and energy analytics environments.

While hybridization does not universally outperform the best standalone model, the proposed DECAW framework offers a theoretically grounded and practically robust advancement in ensemble forecasting methodology for energy demand prediction.

References

[1] N. Roustaei, Application and interpretation of linear-regression analysis, *Medical hypothesis discovery and innovation in ophthalmology* **13** (2024), no. 3, 151–159.

[2] V. Arumugam, V. Natarajan, Time series modeling and forecasting using Autoregressive Integrated Moving Average and Seasonal Autoregressive Integrated Moving Average models, *Instrumentation Mesure Metrologie* **22** (2023), no. 4, 161–168.

[3] J.S. Chou, D.S. Tran, Forecasting energy consumption time series using machine learning techniques based on usage patterns of residential householders, *Energy* **165** (2018), no. B, 709–726.

[4] H. Hamdoun, A. Sagheer, H. Youness, Energy time series forecasting-analytical and empirical assessment of conventional and machine learning models, *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology* **40** (2021), no. 6, 12477–12502.

[5] H.R. Maier, S. Galelli, S. Razavi, A. Castelletti, A. Rizzoli, I.N. Athanasiadis, M. Sanchez-Marre, M. Acutis, W. Wu, G.B. Humphrey, Exploding the myths: An introduction to artificial neural networks for prediction and forecasting, *Environmental Modelling & Software* **167** (2023), 105776.

[6] S. Zhang, J. Liu, J. Wang, High-Resolution Load Forecasting on Multiple Time Scales Using Long Short-Term Memory and Support Vector Machine, *Energies* **16** (2023), no. 4, 1806.

[7] S. Ali, S. Bogarra, M.N. Riaz, P.P. Phyo, D. Flynn, A. Taha, From Time-Series to Hybrid Models: Advancements in Short-Term Load Forecasting Embracing Smart Grid Paradigm, *Applied Sciences* **14** (2024), no. 11, 4442.

[8] S. Baratsas, F. Iseri, E.N. Pistikopoulos, A hybrid statistical and machine learning based forecasting framework for the energy sector, *Computers & Chemical Engineering* **188** (2024), 108740.

[9] E.G.A. Antonini, A. Di Bella, I. Savelli, L. Drouet, M. Tavoni, Weather- and climate-driven power supply and demand time series for power and energy system analyses, *Scientific Data* **11** (2024), 1324.

[10] X. Wen, J. Liao, Q. Niu, N. Shen, Y. Bao, Deep learning-driven hybrid model for short-term load forecasting and smart grid information management, *Scientific Reports* **14** (2024), 13720.

[11] J.P. Mohanty, S. Dash, Forecasting Energy Consumption Using Hybrid CNN and LSTM Auto-Encoder Network with Hyperband Optimization, *International Journal for Research in Applied Science & Engineering Technology (IJRASET)* **10** (2022), no. X, 1041–1055.

[12] I.H. Ou Ali, A. Agga, M. Ouassaid, M. Maaroufi, A. Elrashidi, H. Kotb, Predicting short-term energy usage in a smart home using hybrid deep learning models, *Frontiers in Energy Research* **12** (2024), 1323357.

[13] L. Gasmi, S. Kabou, N. Laiche, R. Nichani, Time series forecasting using deep learning hybrid model (ARIMA-LSTM), *Studies in engineering and exact sciences* **5** (2024), no. 2, e6976.

[14] S.Y. Chou, A. Dewabharata, F.E. Zulvia, M. Fadil, Forecasting Building Energy Consumption Using Ensemble Empirical Mode Decomposition, Wavelet Transformation, and Long Short-Term Memory Algorithms, *Energies* **15** (2022), no. 3, 1035.

[15] R. Mathumitha, P. Rathika, K. Manimala, Intelligent deep learning techniques for energy consumption forecasting in smart buildings: a review, *Artificial Intelligence Review* **57** (2024), 35.
[16] A. Salhi, F. Algarni, R. Alshamrani, A. Althbiti, A. Ismail, M. Basma, Hassan Leveraging artificial intelligence to enable sustainable urban development through the creation of smart and environmentally friendly carbon-free cities, *Scientific Reports* **15** (2025), 35791.
[17] J.O. Ojadi, O.K. Owulade, C.S. Odionu, E.C. Onukwulu, Deep Learning Models for Predicting and Mitigating Environmental Impact of Industrial Processes in Real-Time, *International Journal of Scientific Research in Science, Engineering and Technology* **12** (2025), no. 2, 119–154.
[18] A.R. Singh, M.S. Sujatha, A.D. Kadu, M. Bajaj, H.K. Addis, K. Sarada, A deep learning and IoT-driven framework for real-time adaptive resource allocation and grid optimization in smart energy systems, *Scientific Reports* **15** (2025), 19309.
[19] N. Gholizadeh, P. Musilek, Federated learning with hyperparameter-based clustering for electrical load forecasting, *Internet of Things* **17** (2022), 100470.
[20] V.S.P. Rajulapati, Experimental and Computational Approaches to AI-Driven Load Forecasting and Dynamic Pricing in Smart Grids, *International Journal of Computational and Experimental Science and Engineering* **11** (2025), no. 3.
[21] S.S. Krishna, R. Krishan, Day Ahead Solar Generation Forecasting in Smart Grids to Minimize Electricity Bill, *International Journal for Research in Applied Science & Engineering Technology (IJRASET)* **11** (2023), no. IX, 1230–1256.
[22] J. Pascual, J. Barricarte, P. Sanchis, L. Marroyo, Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting, *Applied Energy* **158** (2015), 12–25.
[23] A. Piacentino, N. Duic, N. Markovska, B. Vad Mathiesen, Z. Guzovic, V. Eveloy, H. Lund, Sustainable and cost-efficient energy supply and utilisation through innovative concepts and technologies at regional, urban and single-user scales, *Energy* **182** (2019), 254–268.
[24] M.A. Mirjalili, A. Aslani, R. Zahedi, M. Soleimani, A comparative study of machine learning and deep learning methods for energy balance prediction in a hybrid building-renewable energy system, *Sustainable energy research* **10** (2023), no. 8.
[25] F. Moazzen, M.J. Hossain, Multivariate Deep Learning Long Short-Term Memory-Based Forecasting for Microgrid Energy Management Systems, *Energies* **17** (2024), no. 17, 4360.
[26] G.E.P. Box, G.M. Jenkins, G.C. Reinsel, G.M. Ljung, Time Series Analysis: Forecasting and Control, *Journal of Time Series Analysis* **37** (2015), no. 5, 709–711.
[27] S. Varma, R. Simon, Bias in error estimation when using cross-validation for model selection, *BMC Bioinformatics* **7** (2006), 91.
[28] V. Assimakopoulos, K. Nikolopoulos, The theta model: a decomposition approach to forecasting, *International Journal of Forecasting* **16** (2000), no. 4, 521–530.
[29] R. Hyndman, A. Koehler, K. Ord, R. Snyder, *Forecasting with Exponential Smoothing*, Springer Series in Statistics, 2008.
[30] R.J. Hyndman, Y. Khandakar, Automatic Time Series Forecasting: The forecast Package for R, *Journal of Statistical Software* **27** (2008), no. 3, 1–22.

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